Text Matching Improves Sequential Recommendation by Reducing Popularity Biases

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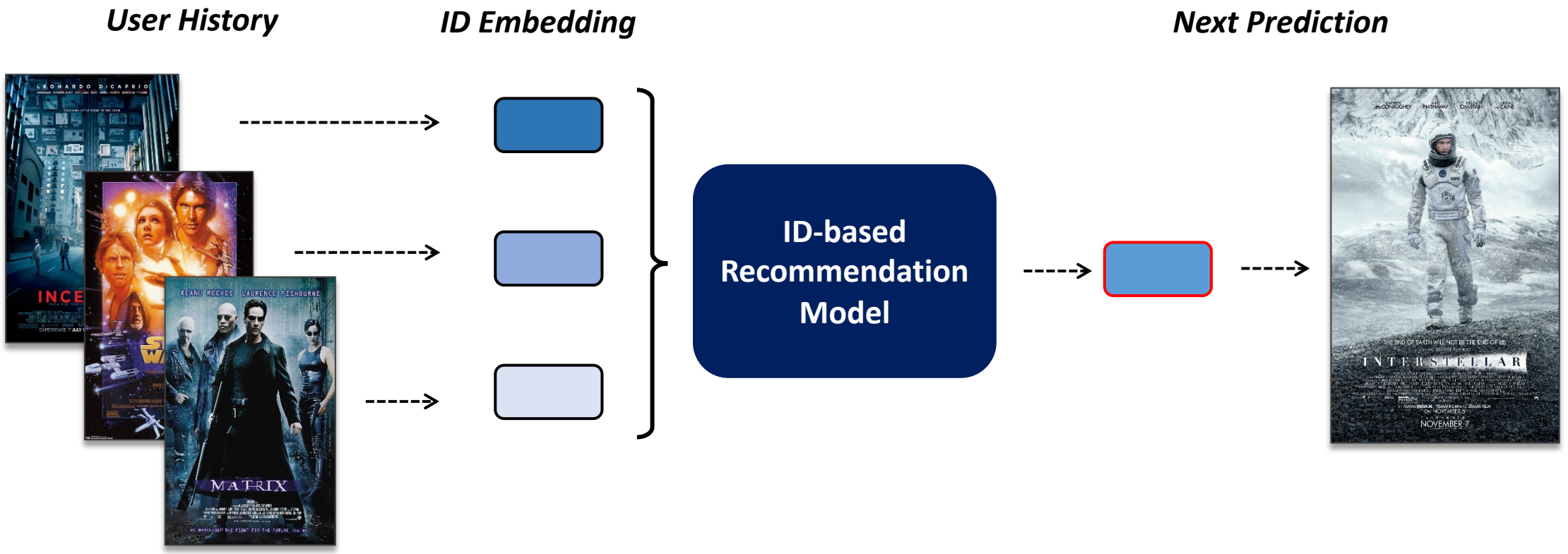
Sequential Recommendation

Sequential recommendation systems aim to

- model user behaviors according to historical interacted items
- recommend the next items for users

Sequential Recommendation

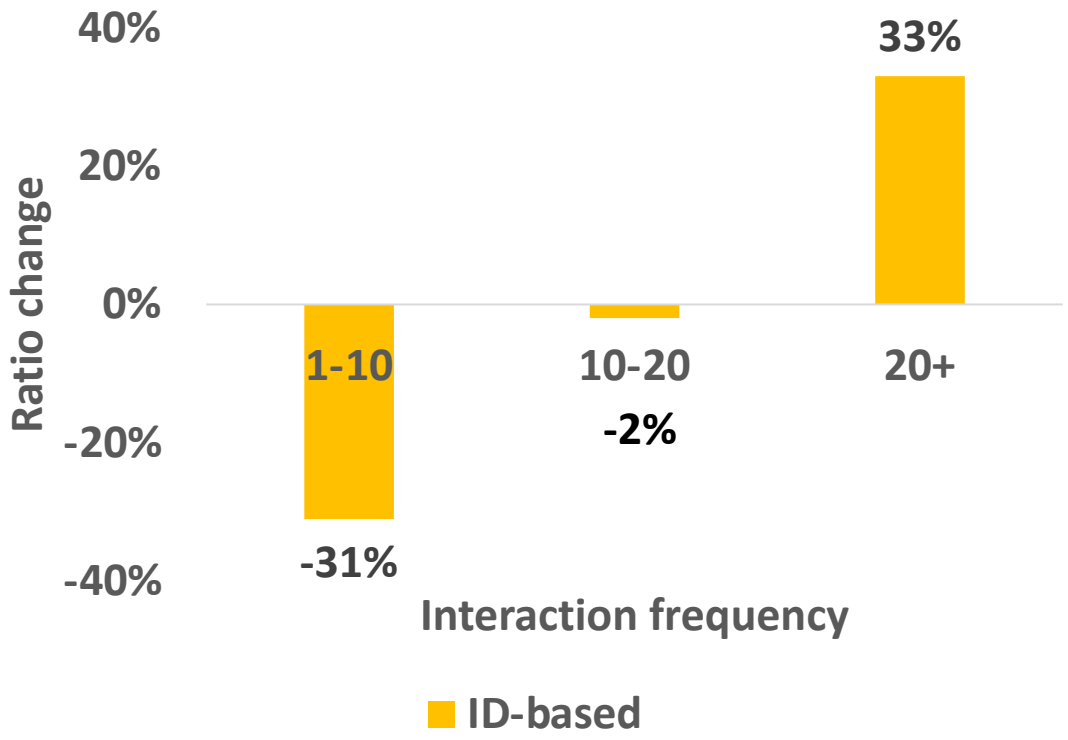
ID-based models represent items using randomly initialized embeddings
e.g. Bert4Rec



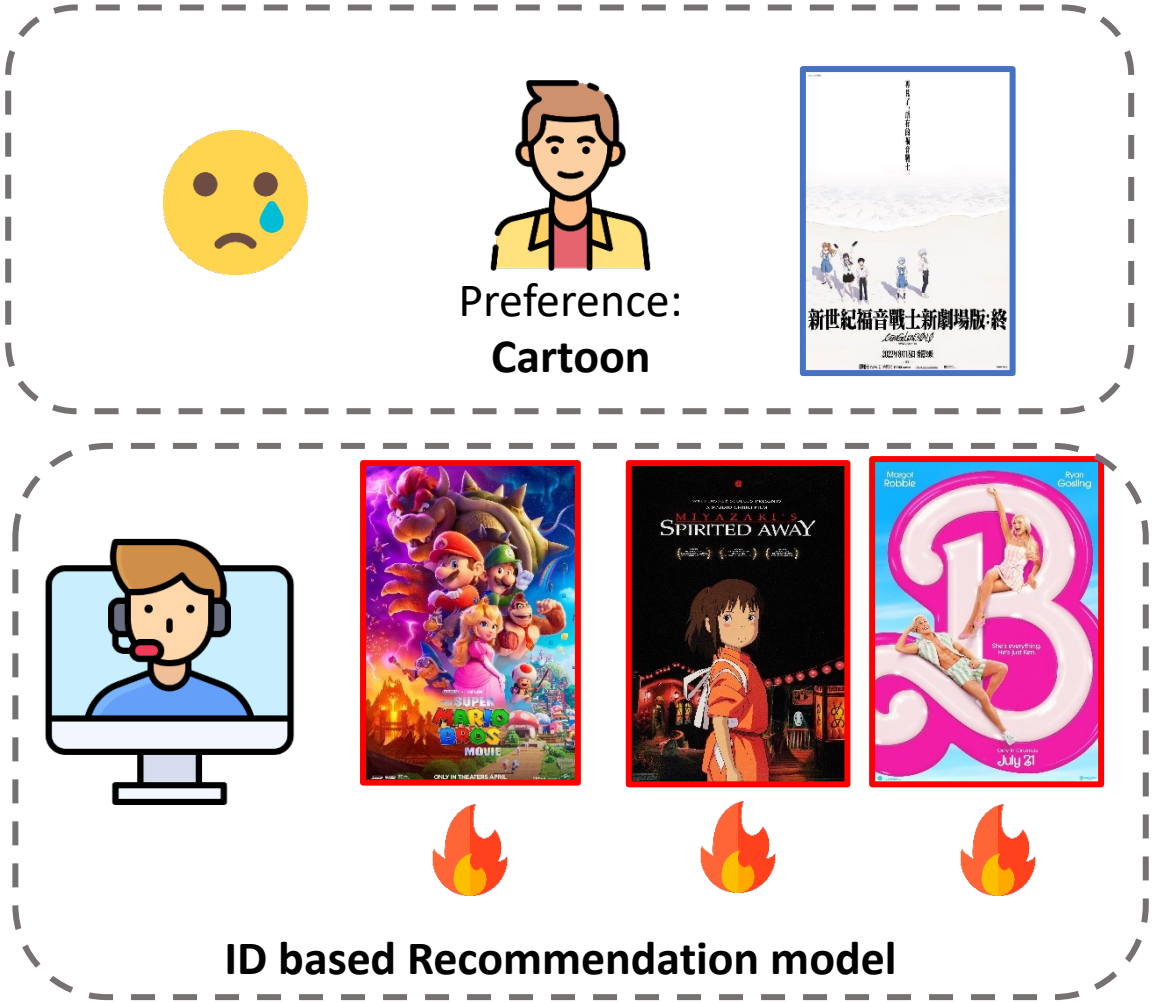
Sun et al. 2019. BERT4Rec: Sequential recommendation with bidirectional encoder representations from transformer. In CIKM.

Popularity Bias

- ID-based models usually tend to recommend popular items
- This behavior doesn't sit well with each user's taste



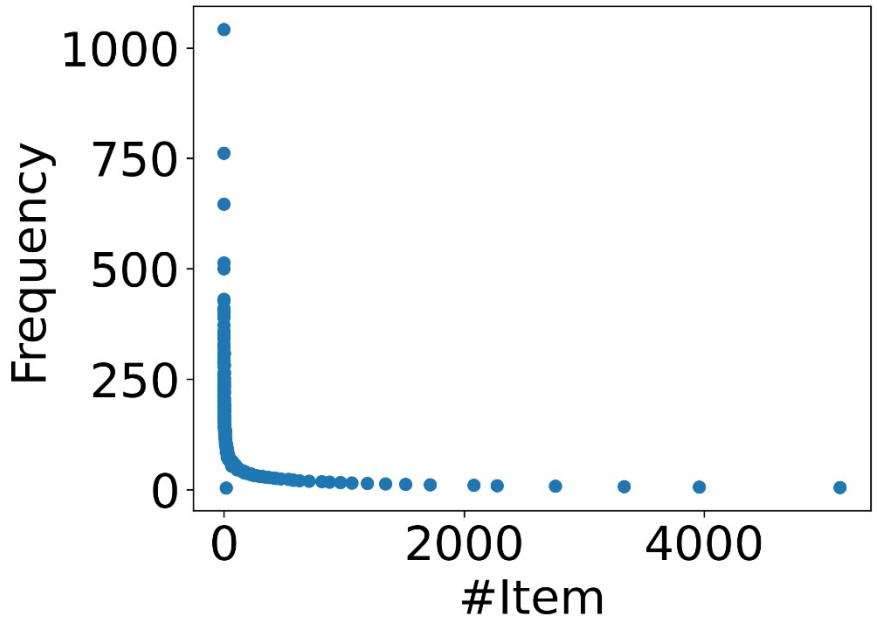
Changes in the proportion of items with different frequencies in Yelp



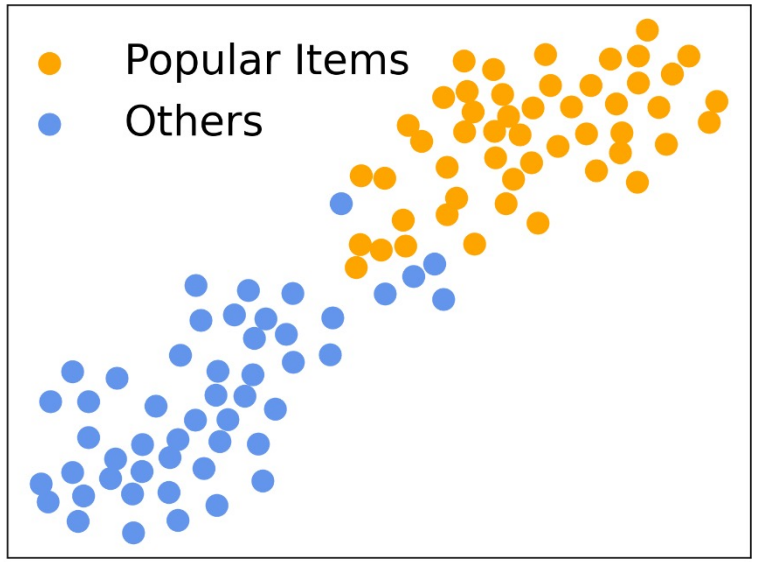
ID based Recommendation model

Reasons for Popularity Bias

- Most items are long-tailed (less user-interacted)
- Return more popular items will win lower training loss
- ID-based recommendation model learns an ununiform embedding space



Item distribution of Amazon dataset

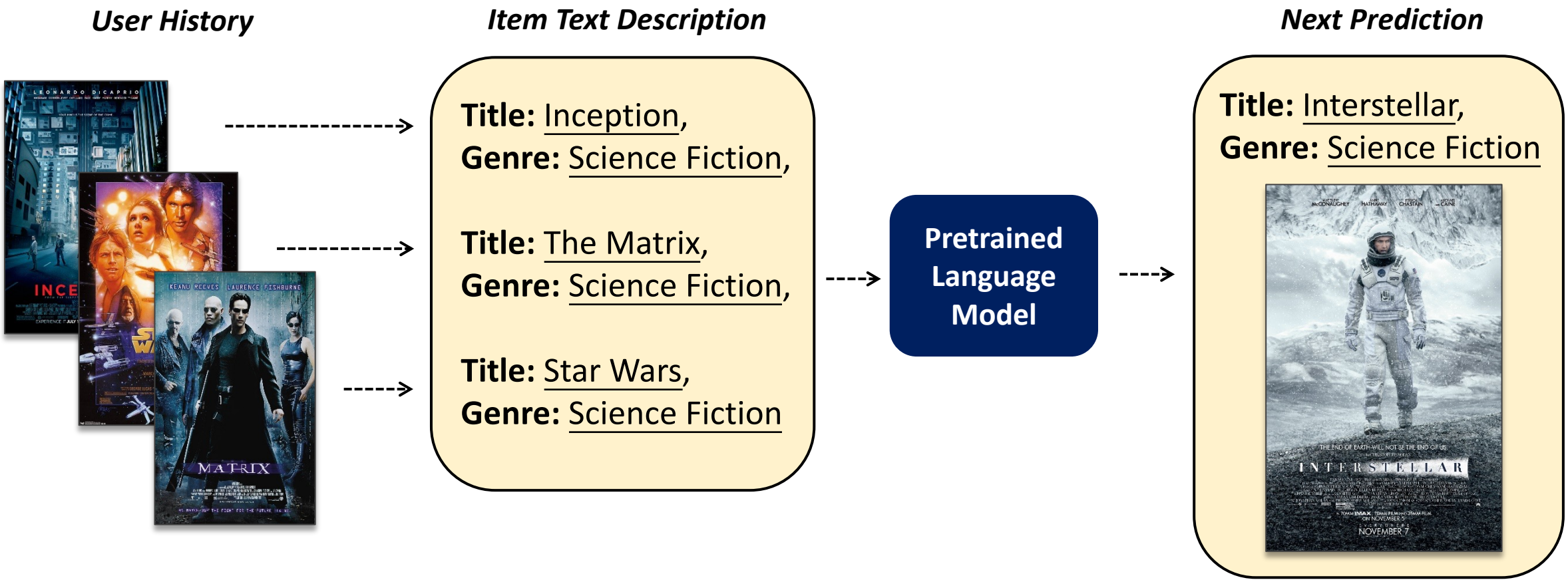


ID-based model embedding space visualization

Sequential Recommendation

Text-based models represent items using the item attributes

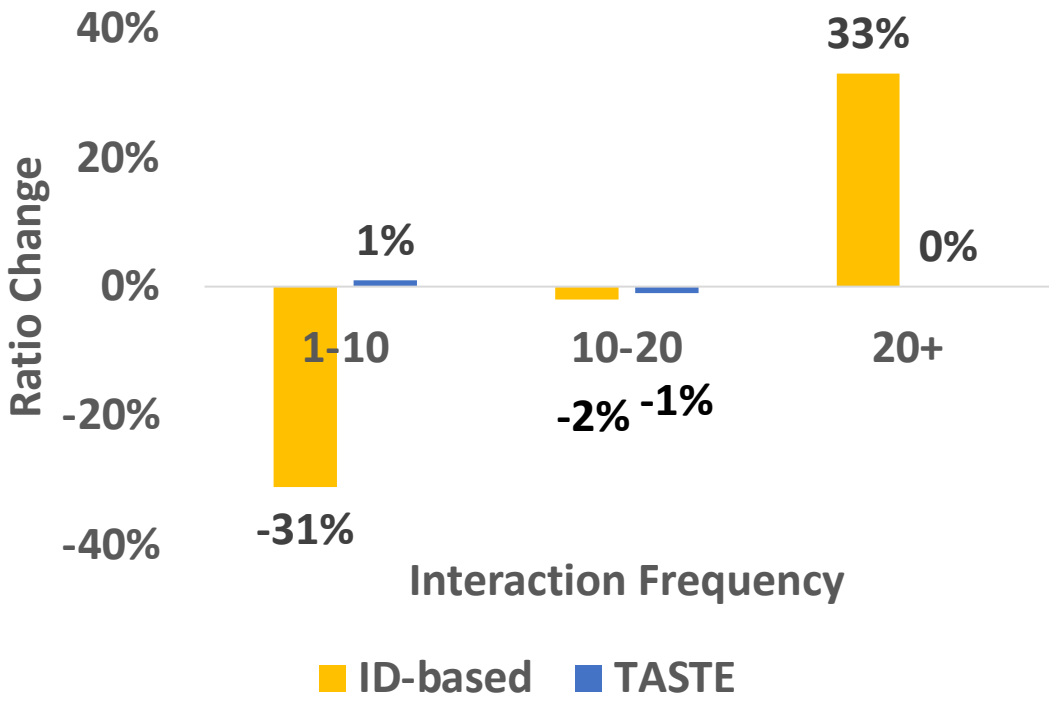
e.g. RECFORMER



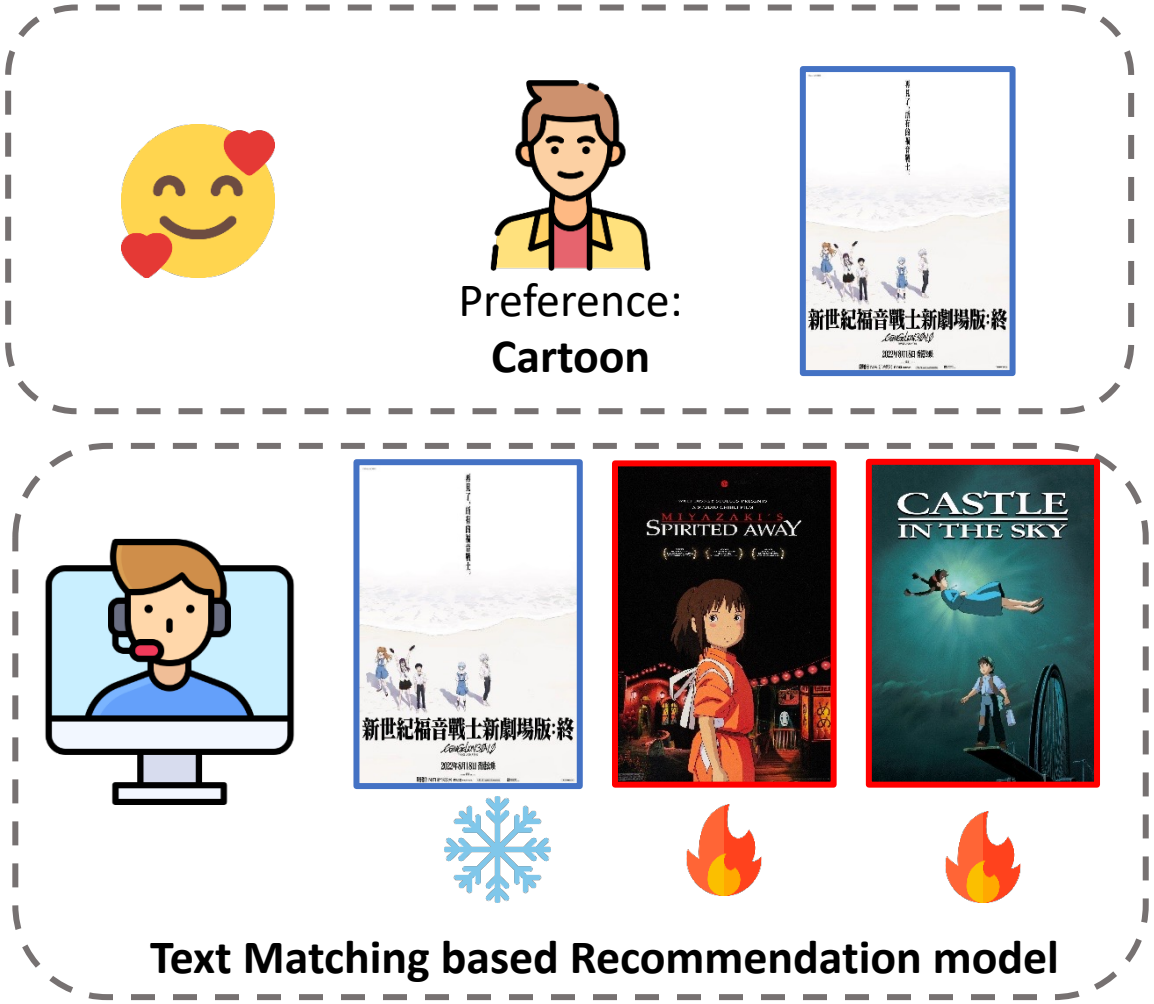
Li et al. 2023. Text Is All You Need: Learning Language Representations for Sequential Recommendation. In KDD.

Text Matching Reduces Popularity Bias

Text matching based model reduces the recommendation of popular items and alleviates the popularity bias problem



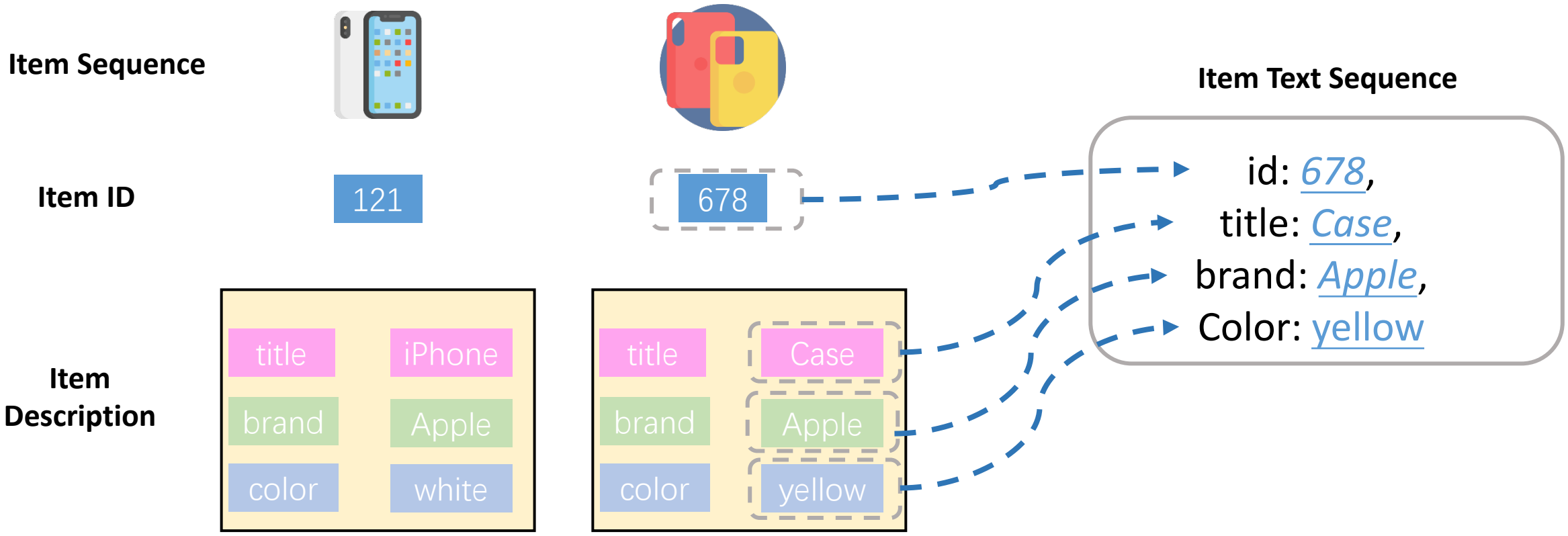
Changes in the proportion of items with different frequencies in Yelp



Text Matching based Recommendation model

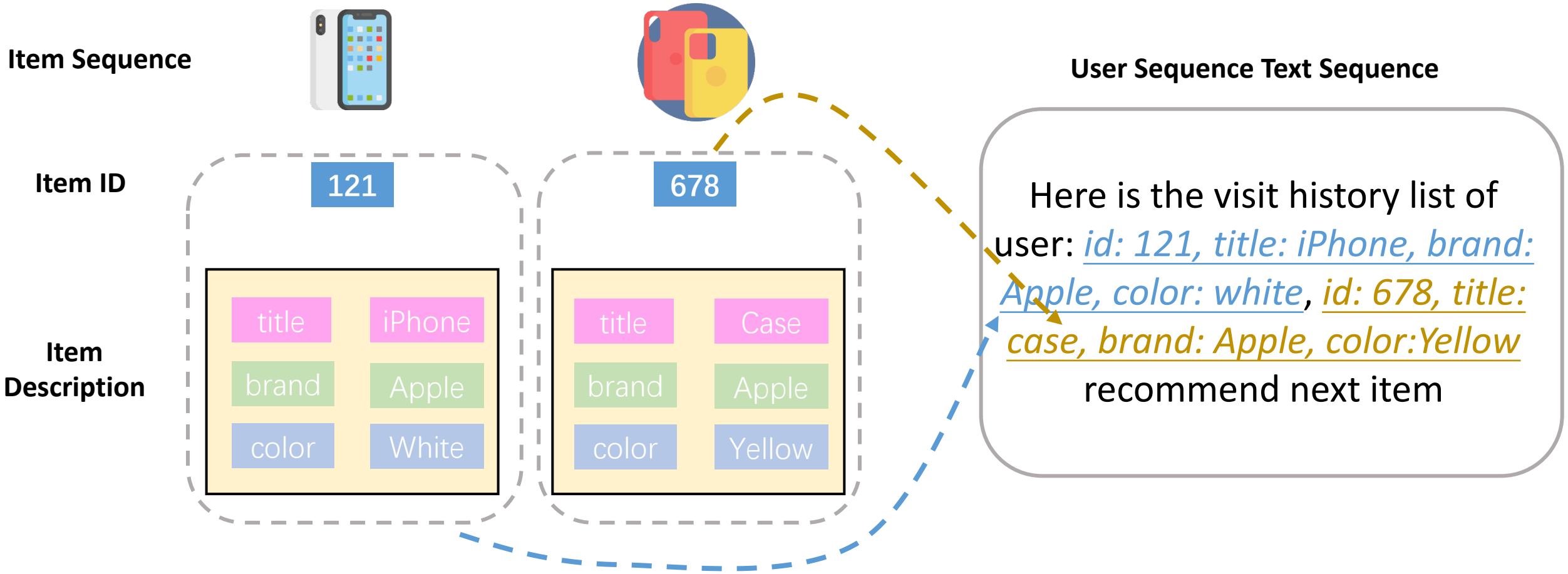
Our Solution

We design templates to represent items using their structural information



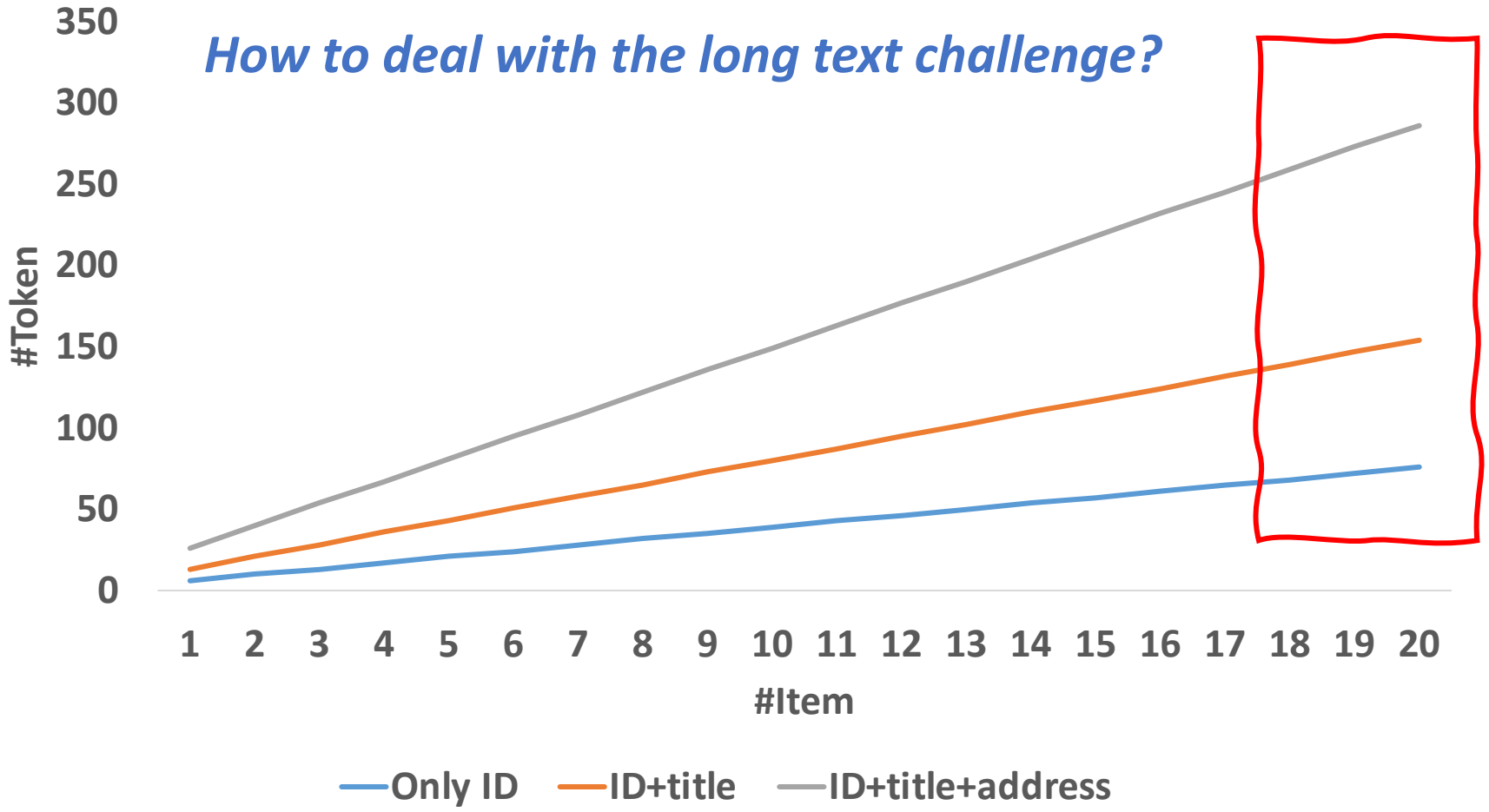
Our Solution

Fill the template with item text sequences in user behaviors to represent users



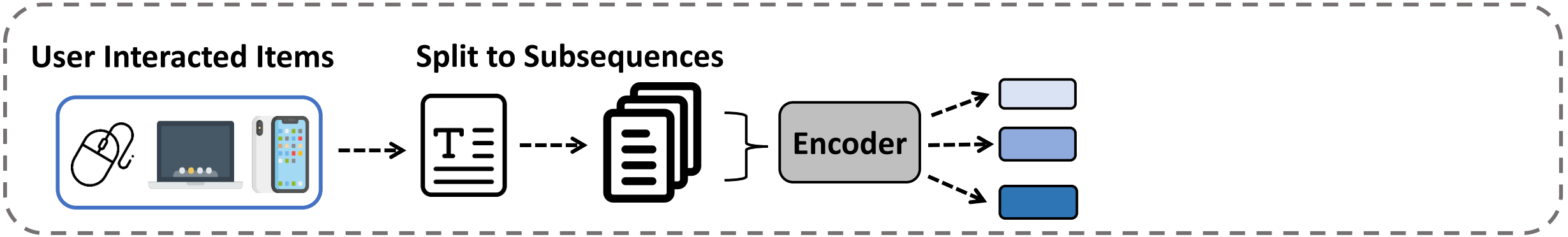
The Long Text Processing Challenge

- Modeling long user behaviors is important to capture user preferences
- However, text representations of users bring long text processing challenge



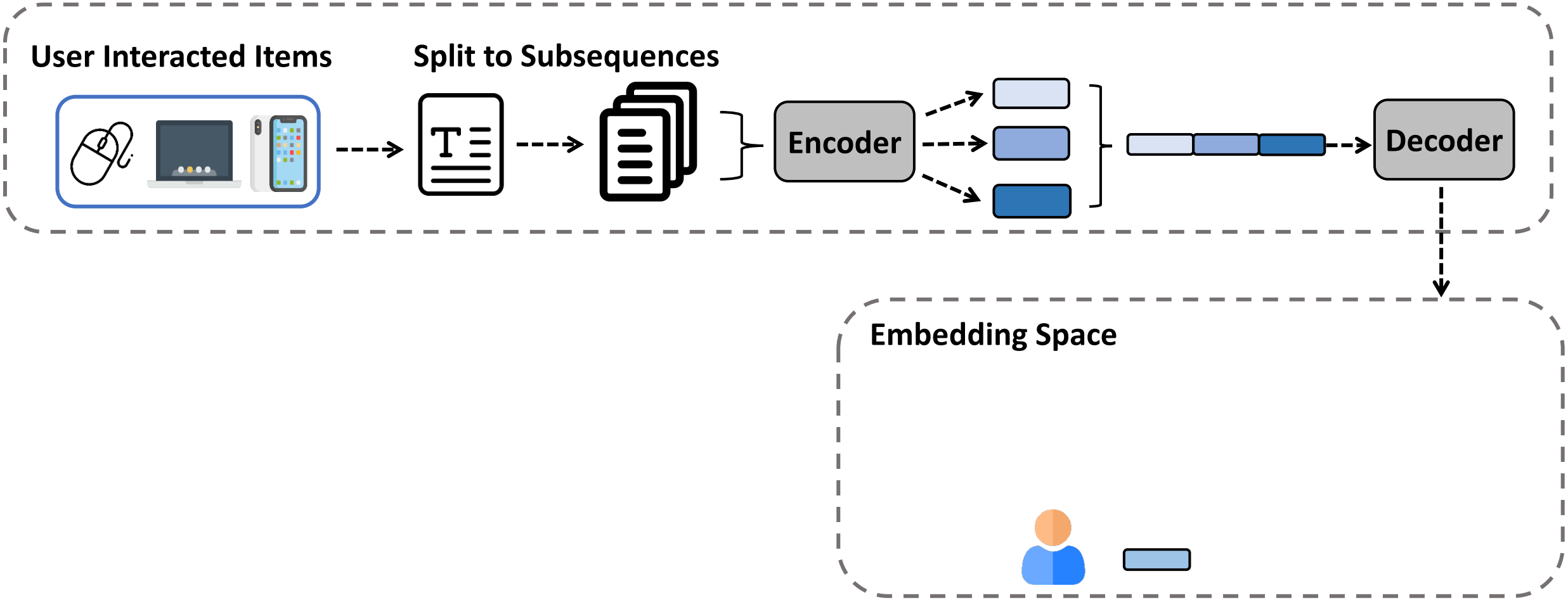
Our Solution

- Split the text representations of users into different subsequences
- Encode them independently using the encoder module



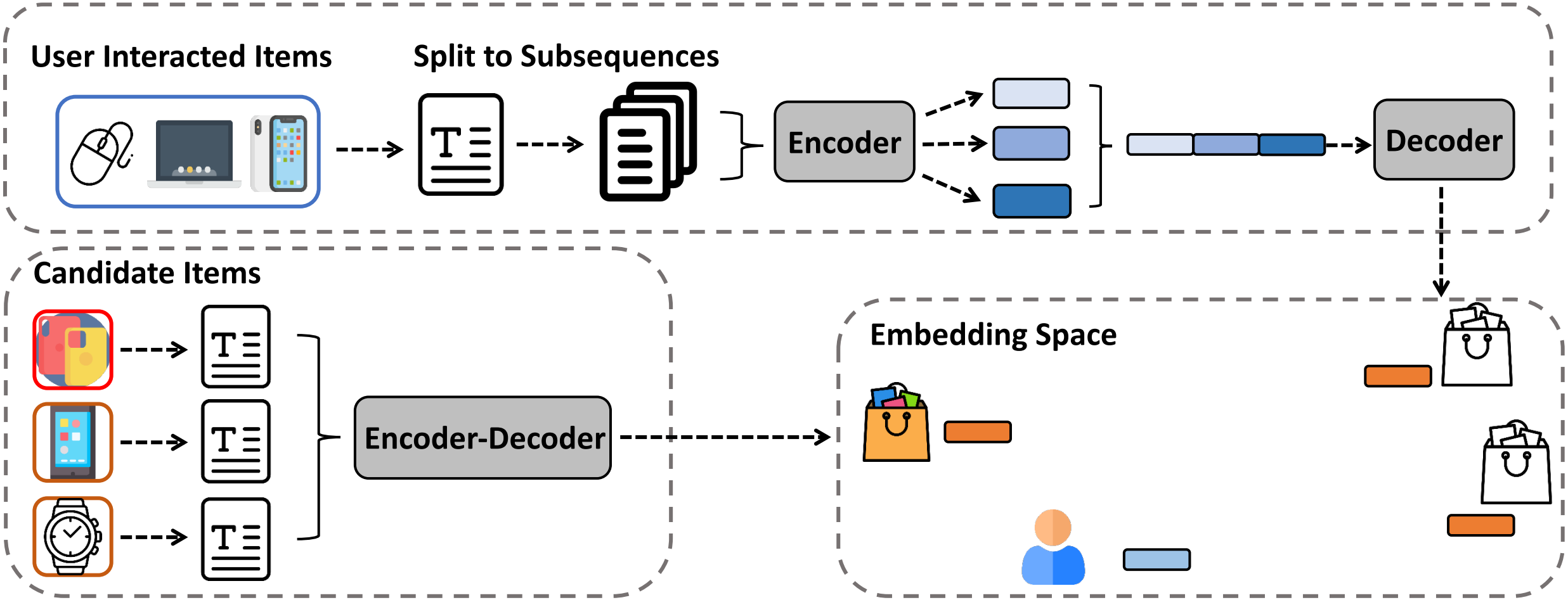
Our Solution

Use the decoder module to capture semantics from different subsequences and finally generate embeddings of users



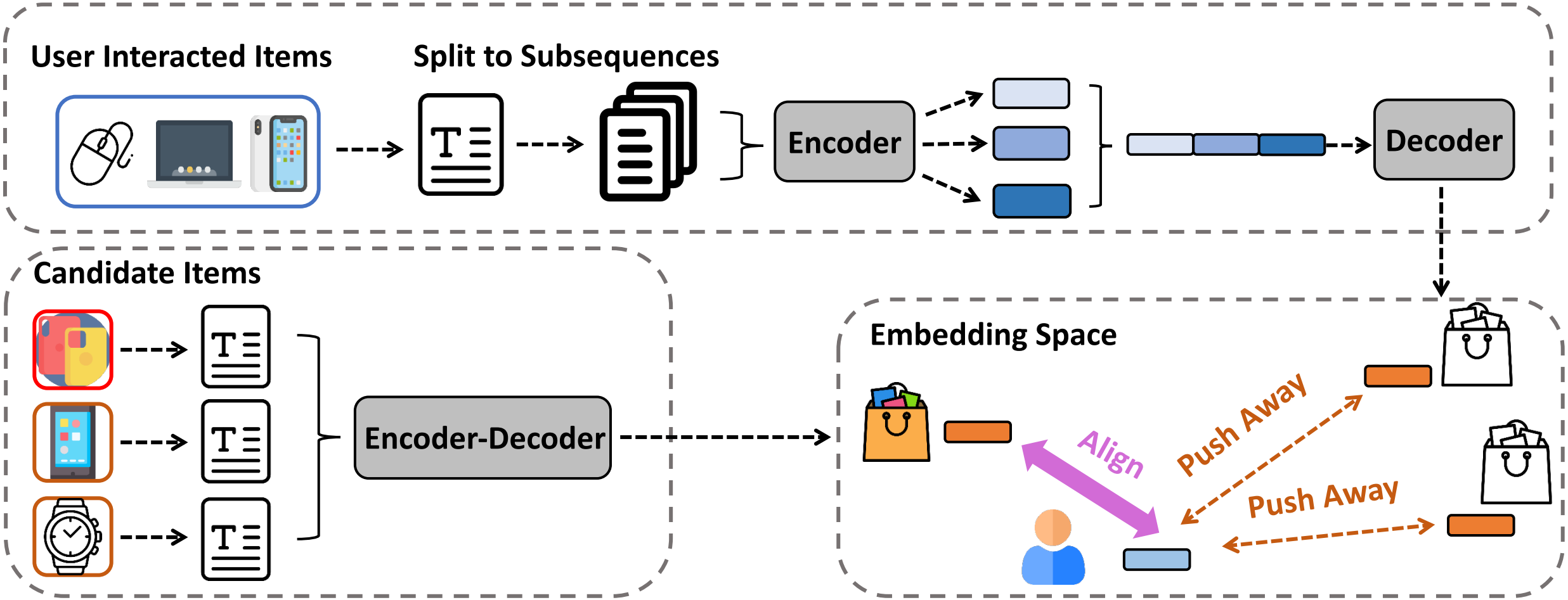
Our Solution

Use the same encoder-decoder architecture to get item embeddings

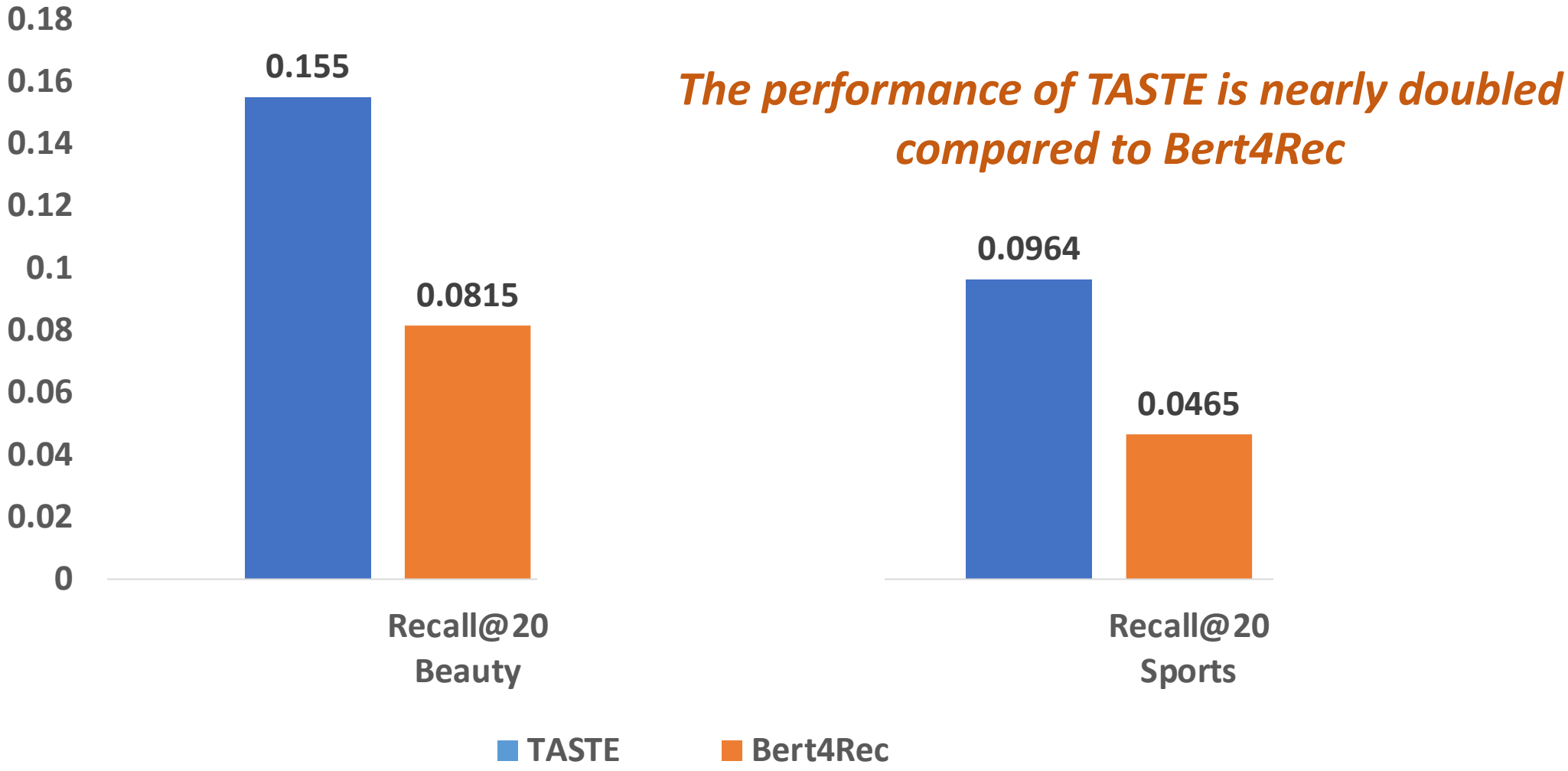


Our Solution

Finally, we train the whole model contrastively using the negatives from in-batch sampling and random sampling

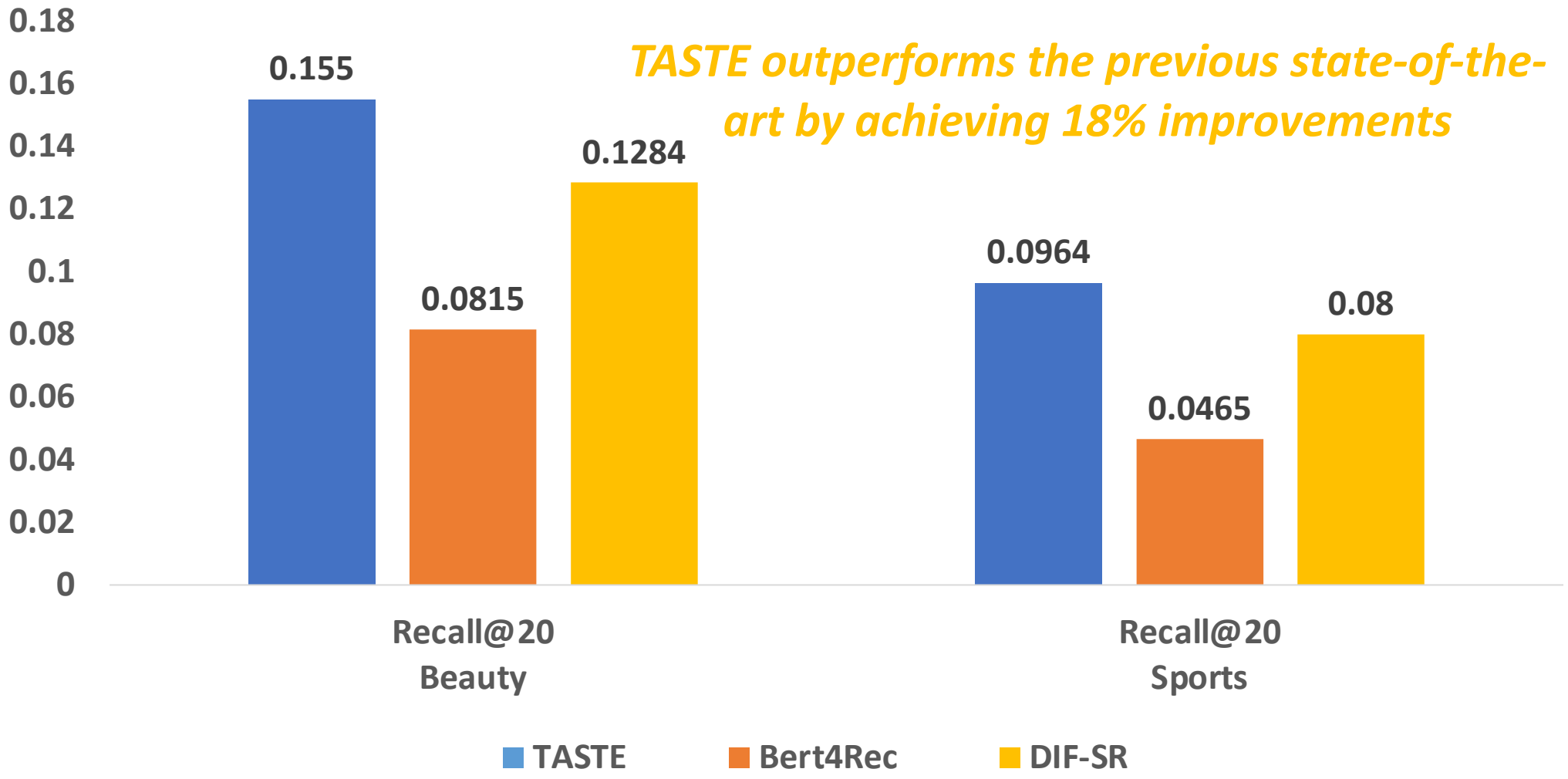


Overall Results



The performance of TASTE is nearly doubled compared to Bert4Rec

Overall Results



TASTE outperforms the previous state-of-the-art by achieving 18% improvements

Incorporate item IDs in TASTE

Which one is better?

ID: **121**,
Title: **iPhone**,
Brand: **Apple**

Method: **Sum the random initialized ID embeddings and text embeddings *(Embed)***

ID: **121**

Random Initialized Embedding

ID Representation

Title: **iPhone**,
Brand: **Apple**

Language Model

Text Representation

Item Emb

Yuan et al.

Method: **Model item ids into the text inputs *(Prompt)***

ID: **121**,
Title: **iPhone**,
Brand: **Apple**

Language Model

Item Emb

Ours

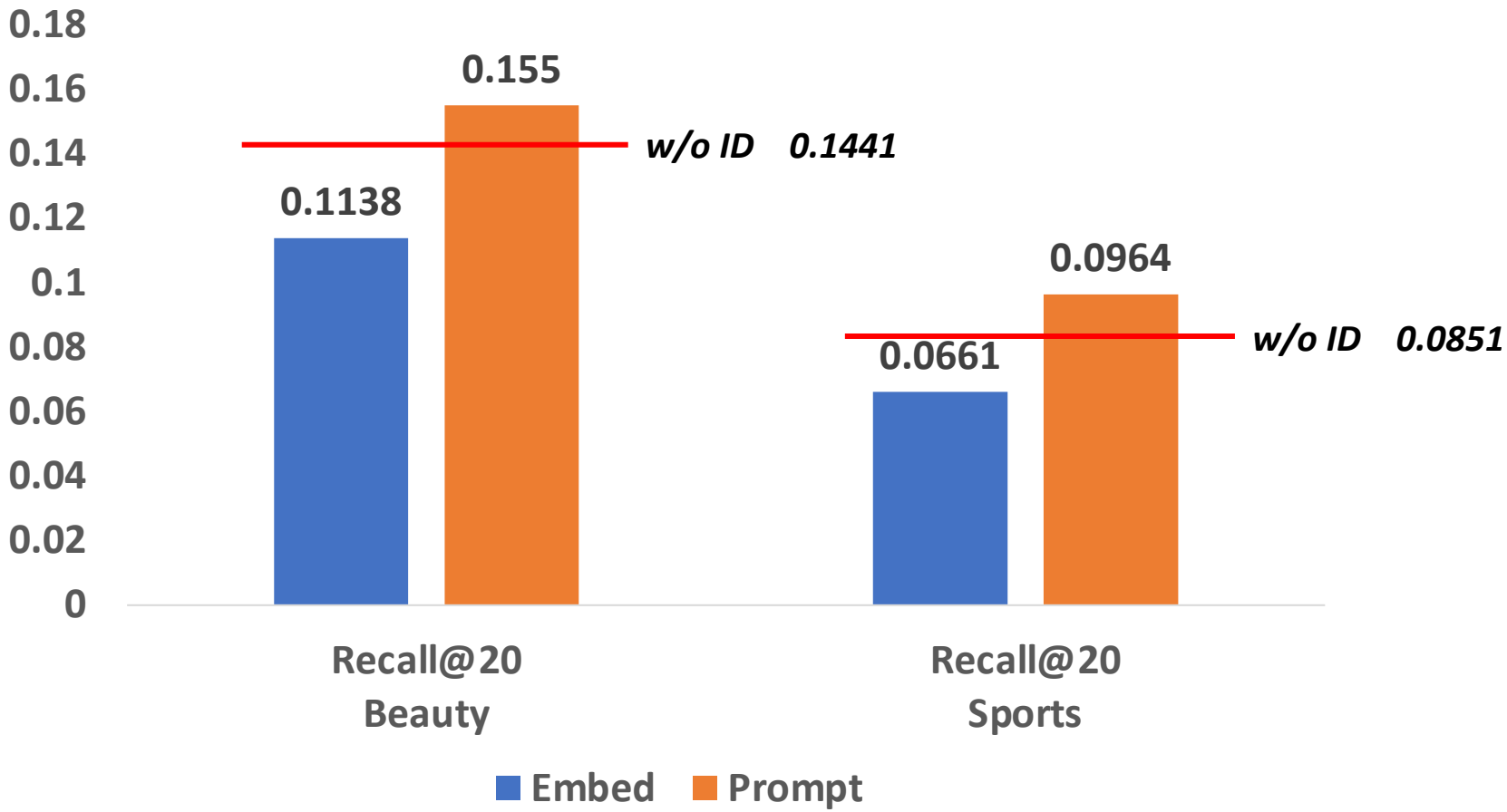
Incorporate item IDs in TASTE

- Item IDs provide additional information to match users and items beyond texts
- The Prompt method outperforms the Embed method

Method: *w/o ID*
- RECFORMER [KDD2023]

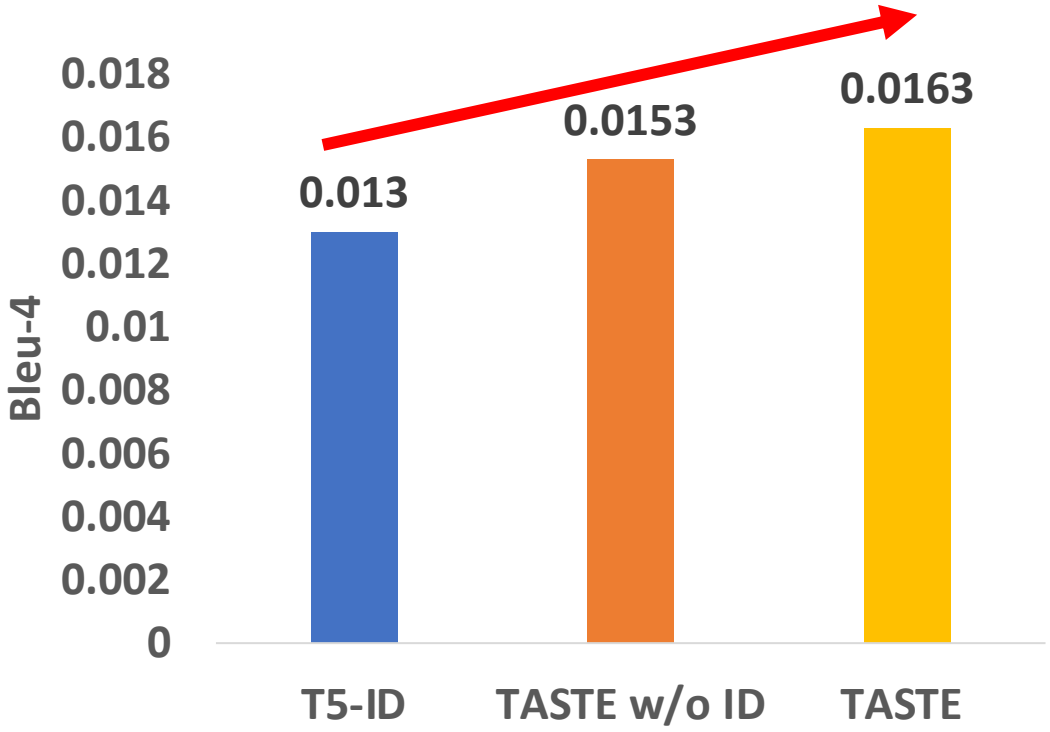
Method: *Embed*
- MoRec [SIGIR2023]

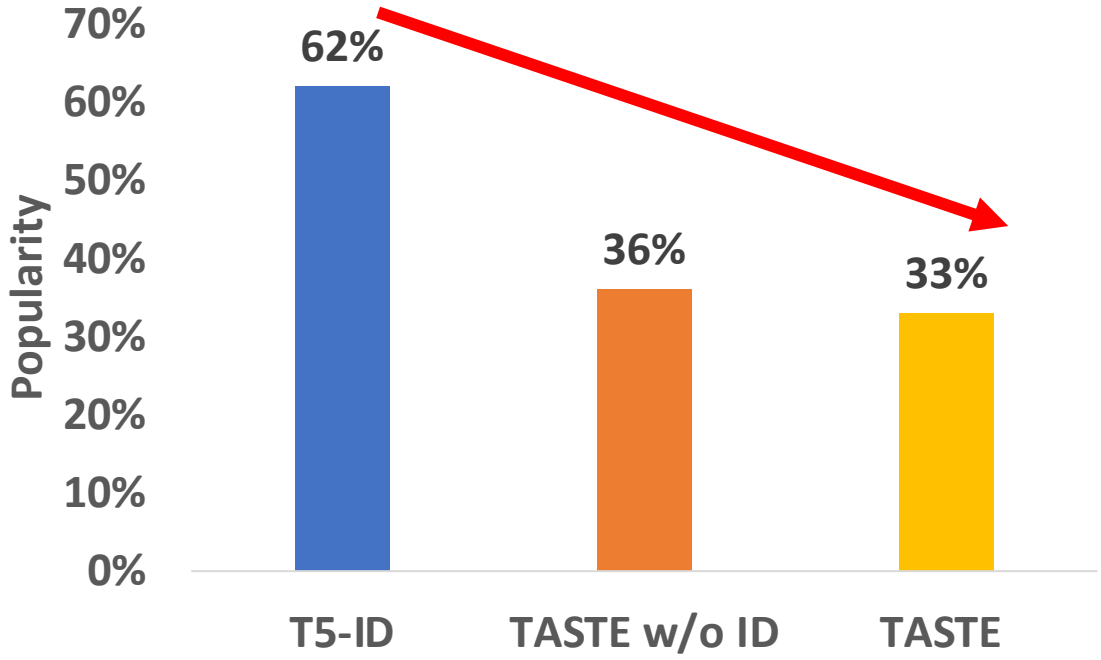
Method: *Prompt*
- TASTE [CIKM2023]



Evaluation on Recommendation Behaviors

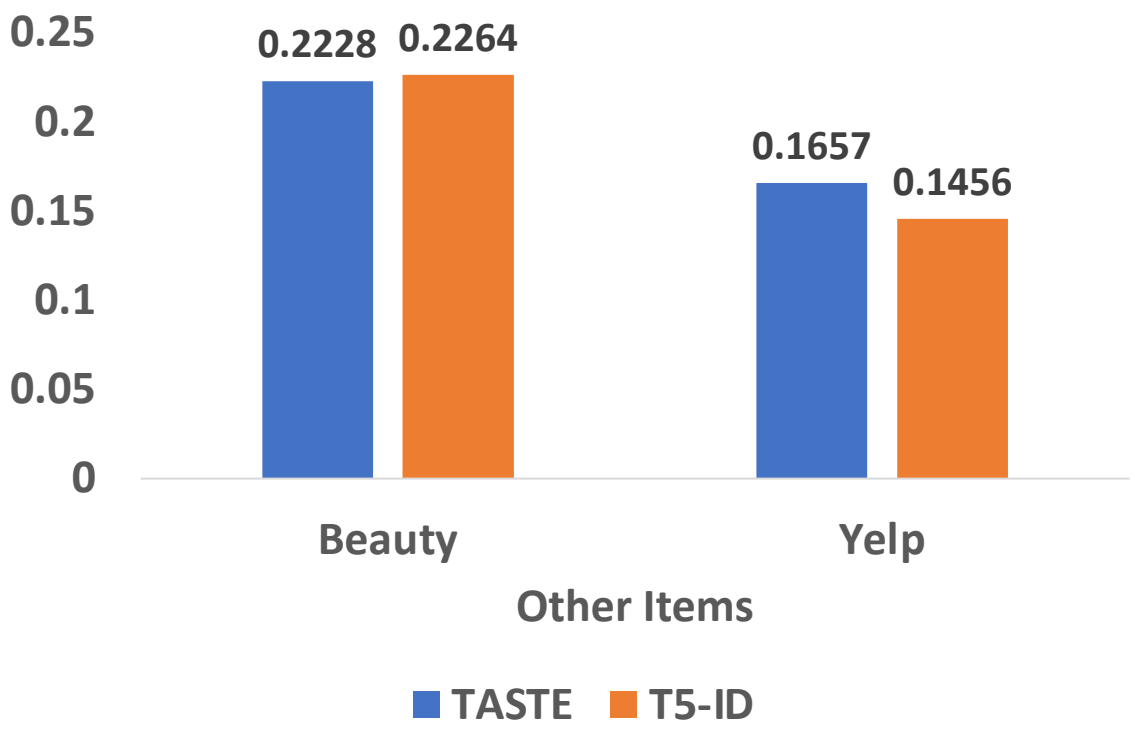
- TASTE benefits from text matching signals and recommends more text-matching items
- This text matching mechanism effectively alleviates the popularity bias problem

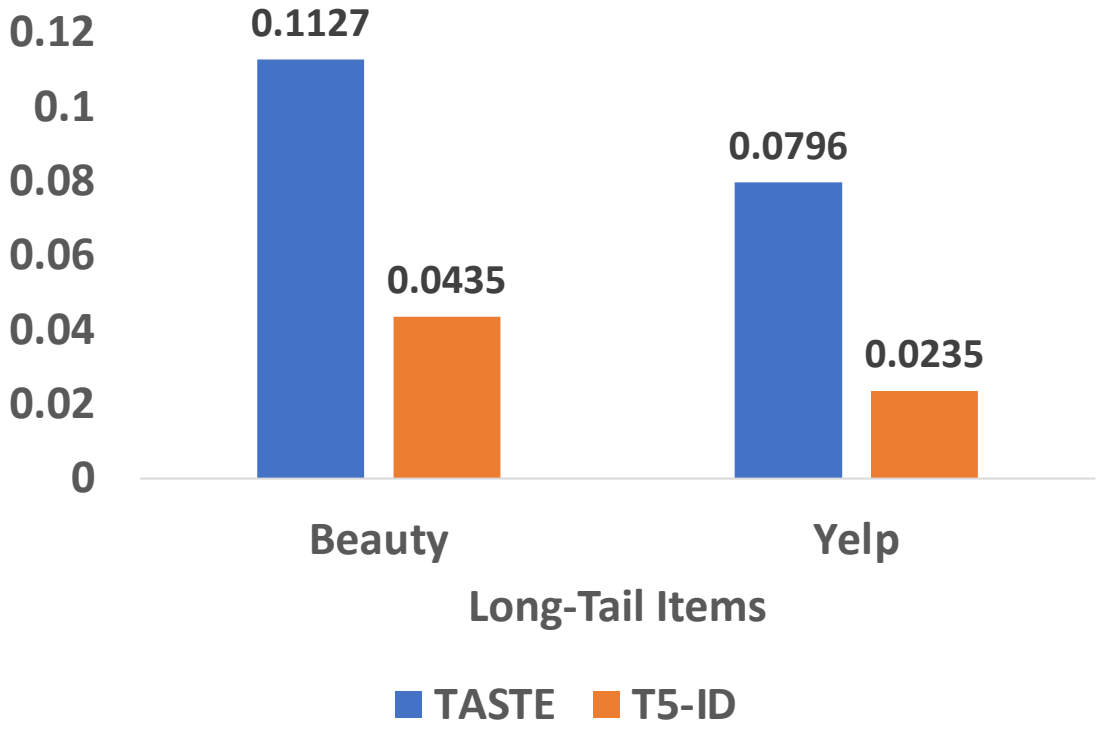




Effectiveness of TASTE on Long-Tail Items

TASTE's performance is almost three times better than the ID-based model in long-tail scenarios, effectively alleviating the cold start problem



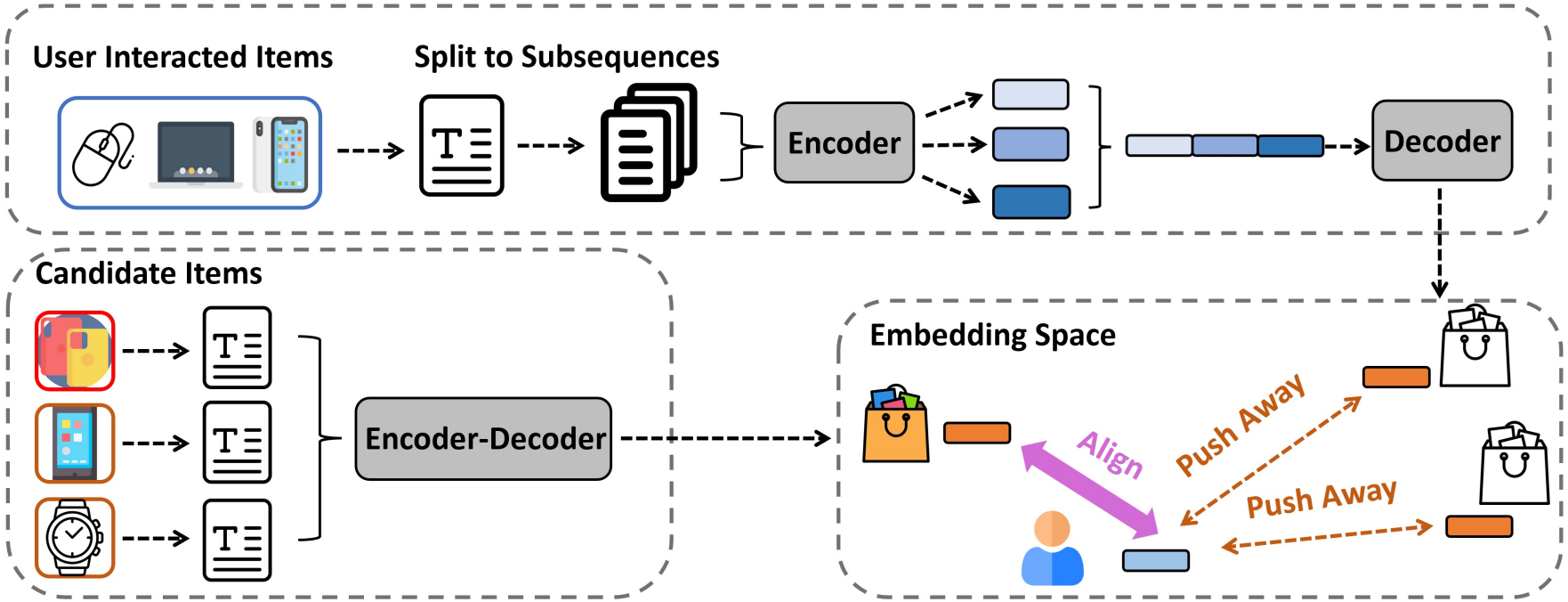


Takeaway

TASTE learns text matching signals to model the relevance between them

TASTE has the ability to better model user behaviors according to long-term user-item interactions

TASTE outperforms previous item id base methods by alleviating the popularity bias



Questions

Paper

Code

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